Power Quality Event Classification Using Hilbert Huang Transform

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Abstract. The objective of this paper is to develop a method based on combination of empirical-mode decomposition (EMD) and Hilbert transform for power quality events classification. Non-stationary power signal disturbance waveform can be considered as superimposition of various undulating modes and EMD is used to separate out these intrinsic modes known as intrinsic mode functions (IMF). Hilbert transform is applied to all the IMF to achieve instantaneous amplitude and frequency. Relevant feature vectors are extracted to do the automatic classification. Time frequency analysis shows clear visual detection, localization and classification of the different power signal disturbances. A balanced neural tree is used to classify the power signal patterns.

Keywords: Non-Stationary power signals, EMD (Empirical Mode Decomposition), Hilbert Transform, Balanced Neural Tree.

1 Introduction

Recently Power Quality (PQ) and related power supply issues have become quite a serious problem both for the end user as well as the utilities. The PQ issues and related phenomena can be attributed to the use of solid-state switching devices, unbalanced and non-linear loads etc. These devices introduce distortions in the phase, frequency and amplitude of the power system signal thereby deteriorating PQ. Hence analysis of PQ related issues are indispensable and this has been the focus of the researchers in the past decade. Time–frequency analysis has been successfully used in dealing with rapidly varying transient signals [1].

The time–frequency transform would provide direct information about the frequency components occurring at any given time. *Fourier Transform* tells us what frequency components are present but do not tell us when it happens and for how long. Although FT is one of the fast technique but its efficiency is limited to stationary signals only. Most PQ events are non-stationary and hence require technique that would not only provide frequency information but also capture the timing of occurrence of the disturbance. *Short Time Fourier Transform* provides frequency as well as time information. The non-stationary nature of the signal is well defined. However, due to the constant window length, some characteristics of the signal are not detected well. Different types of disturbances would require windows of different length. Choosing the best window length could be a problem.

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Wavelet Transform [2] provides time and frequency information of the signal by convolving the dilated and translated wavelet with the signal. By allowing variations in time and frequency plane, a multi-resolution analysis can be obtained. The main disadvantage of wavelet transform is its degraded performance under noisy situation. *Stockwel Transform* most commonly known as S-transform is yet another technique which is being widely used by PQ engineers. The S-transform is an extension of wavelet transform and is based on localizing Gaussian window. Here, the modulating sinusoids are fixed with respect to time axis while the Gaussian window scales and moves [3].

Current advances in signal analysis have led to the development of a new method for non-stationary signal analysis called *Hilbert Huang Transform (HHT)*. Together, the EMD and the Hilbert transform are labeled as the Hilbert-Huang transform. In the proposed work, clear visual localization, detection has been investigated thoroughly for each of the power signal disturbances using HHT.

2 Empirical Mode Decomposition

This work presents a new data analysis method based on the Empirical Mode Decomposition (EMD) method, which will generate a collection of intrinsic mode functions (IMF). The decomposition is based on the direct extraction of the energy associated with various intrinsic time scales. Expressed in IMFs, they have well-behaved Hilbert transforms, from which the instantaneous frequencies can be calculated. Thus, we can localize any event on the time as well as the frequency axis.

In general, signals will consist of more than one oscillatory component. The idea of the EMD [4] is to repeatedly apply a process known as sifting to separate out the fastest oscillatory mode, then the next fastest, and so on until the signal has been entirely broken down into simple oscillatory components, which Huang calls intrinsic mode functions (IMFs).

An *Intrinsic Mode Function (IMF)* is a function that satisfies two conditions:

1. For a data set, the number of extrema and the number of zero crossings must be either equal or differ at most by one.
2. At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The detailed description of the sifting process is given step wise:

1) The decomposition method requires use of envelopes defined by the local maxima and minima separately.
2) After identifying the local extrema, cubic spline functions are used for connecting local maximas as the upper envelope and local minimas as the lower envelope.
3) The mean value of envelopes is defined as M_1. The difference between the original data and M_1 is the first component K_1.

$$X(t) - M_1 = K_1. \tag{1}$$

4) If K_1 satisfies the two IMF conditions then K_1 is the first IMF else if K_1 is not an IMF then it is treated as original signal and steps from (1) to (3) are repeated to get component K_{11}.

$$K_1 - M_{11} = K_{11}. \tag{2}$$

5) After repeated sifting i.e. up to n times, K_{1n} becomes an IMF

$$K_{1(n-1)} - M_{1n} = K_{1n}. \tag{3}$$

Then it is designated as
$$C_1 = K_{1n}. \tag{4}$$

6) C_1 is the first IMF component from the original data. Separate C_1 from *X(t)*

$$R_1 = X(t) - C_1. \tag{5}$$

7) Now treating R_1 as the original data and repeating the above processes second IMF can be obtained.
8) The above procedure is repeated *q* times and *q* IMFs of signal *X(t)* are obtained.
9) The decomposition process can be stopped when R_q becomes a monotonic function from which no more IMF can be extracted.

The essence of the method is to identify the intrinsic oscillatory modes by their characteristic time scales in the data empirically, and then decompose the data accordingly.

Simulation Results. In our study we have discussed different types of practical and synthetic power signal problems such as voltage sag, voltage swell, momentary interruption, harmonics, flicker, multiple notches, multiple spikes and transients which are analyzed with MATLAB software. The EMD output shows the plot of the IMF Components in fig-1&2 which are obtained by the decomposition of a given input signal.

3 Hilbert Transform

The Hilbert transform is commonly used to generate a complex time series or analytic signal. The benefit is that instantaneous attributes can be derived from complex traces [5]. However, accurate and meaningful computation of these attributes requires that the input signal's start and end have zero amplitude, and it contains no trend that introduces a nonzero mean. In this regard, perhaps the most significant seismic use for the EMD is to prepare a signal for input to the Hilbert transform. The conventional Hilbert transform of a continuous signal *x(t)* is:

$$y(t) = \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau. \tag{6}$$

The transfer function of the discrete Hilbert transform is defined as:

$$H(\omega) = \begin{cases} j, 0 < \omega < \pi \\ 0, \omega = 0 \,\&\, \omega = \pi \\ -j, -\pi < \omega < 0 \end{cases} \tag{7}$$

The method for computing the discrete Hilbert transform is based upon its transfer function and utilizing the discrete Fourier transform (DFT) as a tool. Steps for Hilbert transform calculation are:

1) Compute the DFT of the signal *x(n)* where *n=1, 2…N, X(k) = DFT [x(n)].*
2) *X* is multiplied by the mask *H* where *H* is defined as
   H = {0, j, j…0,-j,-j……..-j} if n is even.
   H = {0, j, j…j,-j,-j……..-j} if n is odd.
3) Compute the inverse DFT to obtain *x = IDFT [X.*H].*

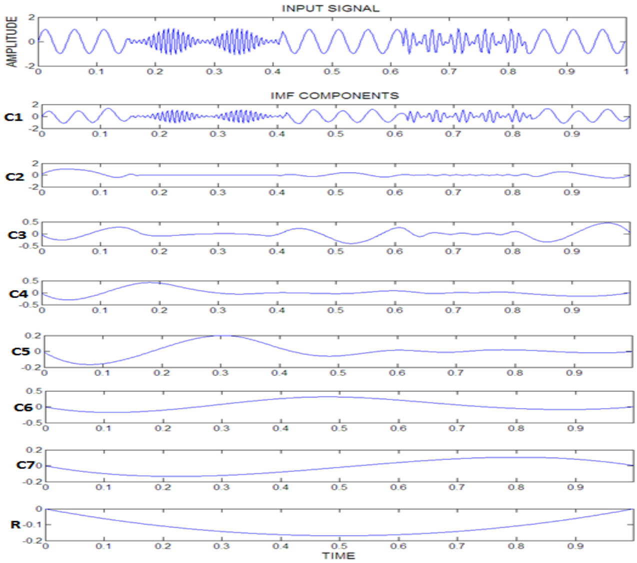

Fig. 1. Decomposition of the Signal with Flicker and Harmonics

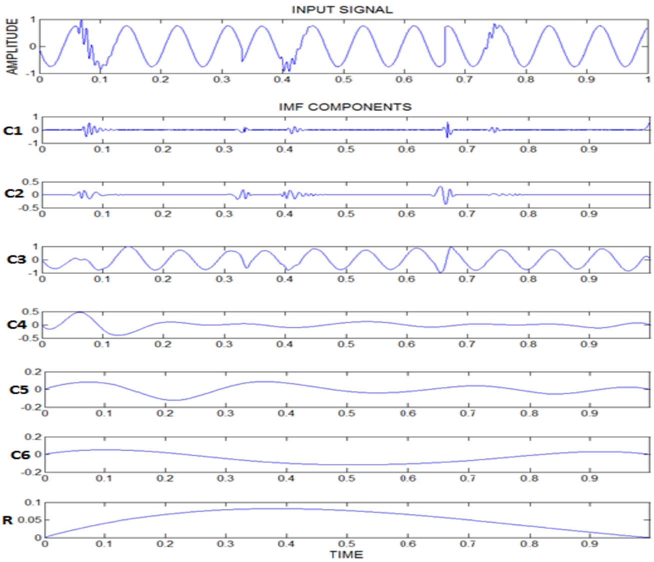

Fig. 2. Decomposition of the signal with multiple disturbances

Non-Stationary signal may not be represented well by sinusoidal components and since frequency is defined well for sinusoidal components it loses its effectiveness for non-stationary signal. This has given rise to notion of *Instantaneous Frequency.* Instantaneous Frequency (IF) has a meaning for mono-component signal, comprising of a single frequency or a narrow band of frequencies. This motivates to decompose a signal into number of mono-component modes for which IF can be defined. The Hilbert Transform of the signal *X(t)* results in an analytical signal *Z(t)* defined as:

$$Z(t) = X(t) + jY(t) = a(t)e^{j\theta(t)}.$$

In which $a(t) = \left[X(t)^2 + Y(t)^2\right]^{1/2}$, $\theta(t) = \arctan\left(\frac{Y(t)}{X(t)}\right)$. **(8)**

Where *Y(t)* is Hilbert transformed signal, *a(t)* is instantaneous amplitude and $\theta(t)$ is instantaneous phase. The analytic signal *Z(t)* has a real part *X(t)* which is the original data, and an imaginary part *Y(t)* which contains the Hilbert transform. The imaginary part is a version of the original real sequence with a 90° phase shift. The Hilbert transformed series has the same amplitude and frequency content as the original real data and includes phase information that depends on the phase of the original data. The instantaneous amplitude is the amplitude of the complex Hilbert Transform; the IF is the time rate of change of the instantaneous phase angle. IF is evaluated as:

$$\omega = \frac{d\theta}{dt}. \quad \textbf{(9)}$$

IF given in the above equation is a single valued function of time. At any given time, there is only one frequency value; therefore, it can only represent one component, hence 'mono-component'. This motivates to extract the mono-component signals (IMFs) from the original signal.

4 Hilbert Spectrum

Hilbert spectrum provides an intuitive visualization of what frequencies occurred during the signal duration, and also shows at a glance where most of the signal energy is concentrated in time and frequency plane. It would be ideal for non-stationary data analysis. After performing the Hilbert transform on each IMF component, we can express the data in the following form:

$$X(t) = \sum_{i=1}^{n} a_i(t)e^{j\theta_i(t)} = \sum_{i=1}^{n} a_i(t)\exp\left(j\int \omega_i(t)dt\right). \quad (10)$$

Above equation enables us to represent the amplitude and the IF as functions of time in a three-dimensional plot, in which the amplitude can be contoured on the time-frequency plane. This time-frequency distribution of the amplitude is designated as the Hilbert amplitude spectrum *H(w,t),* or simply Hilbert spectrum. If squared amplitude is more desirable, commonly to represent energy density, then the squared values of amplitude can be substituted to produce the Hilbert energy spectrum.

Simulation Results. This section presents the HHT output which shows the plot of the Energy spectrum, Magnitude response of a given input signal in the time-frequency co-ordinate system. Here the Hilbert Energy Spectrum is plotted in a time-frequency plane where the energy concentration is represented in terms of intensity of the color shown in fig-3&4.

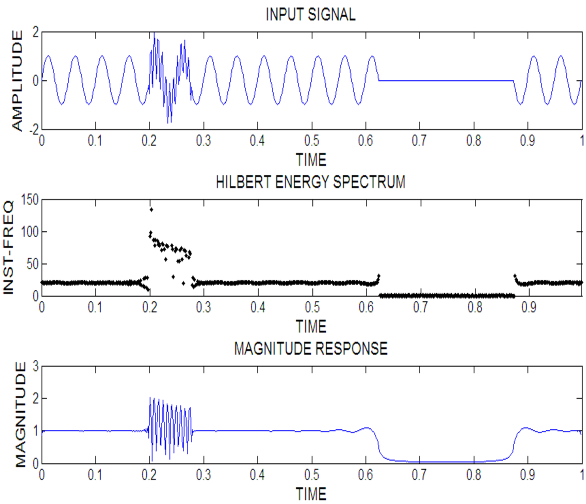

Fig. 3. Detection and visual localization of the Signal with Transient and Mom-Interruption

5 Balanced Neural Tree

In this work a new NT architecture called Balanced NT (BNT) [6] is proposed to reduce the size of the tree (both in depth and in the number of nodes), and to improve the classification of PQ events with respect to a standard NT [7]. To achieve this result, two main improvements are proposed: (a) *Perceptron Substitution* which aims to balance the tree structure by substituting the last trained perceptron with a new perceptron that equally distributes the patterns among the classes, if the current training set is largely misclassified into a reduced number of classes and (b) *Pattern Removal* consists of the introduction of a new criterion for the removal of tough training patterns that cause an over-fitting problem. The proposed novelties aim to define a new training strategy that does not require the definition of complex network topologies [8]. Two main phases can be distinguished, training phase and classification phase.

In the training phase [9], the BNT is constructed by partitioning a training set consisting of feature vectors and their corresponding class labels to generate the tree in a recursive manner. The perceptron [10,11] is trained with the patterns of the TS until the variation of a given error $\bar{e}$ remains in the range [-*toler*, +*toler*] for more than a given number *wait* of epochs. Let us define the error $\bar{e}$ as the mean error computed on all output neurons and patterns,

$$\bar{e} = \frac{1}{QM}\sum_{q=1}^{Q}\sum_{i=1}^{M} e_i^q \quad (11)$$

Where Q is the total number of patterns at the current node and the error e_i^q is the difference of output o_i^q and the target's class t_i^q which are computed as follows:

$$e_i^q = t_i^q - o_i^q, i = 1,\ldots, M . \quad (12)$$

And

$$t_i^q = \begin{cases} 1 \text{ If } & i = i_q \\ 0 \text{ Otherwise} \end{cases}, \qquad o_i^q = 1\Big/\left[1+\exp\left(-\sum_{j=1}^{N} w_{ij}x_j^q\right)\right]. \quad (13)$$

Where w_{ij} are the elements of the weight matrix W.

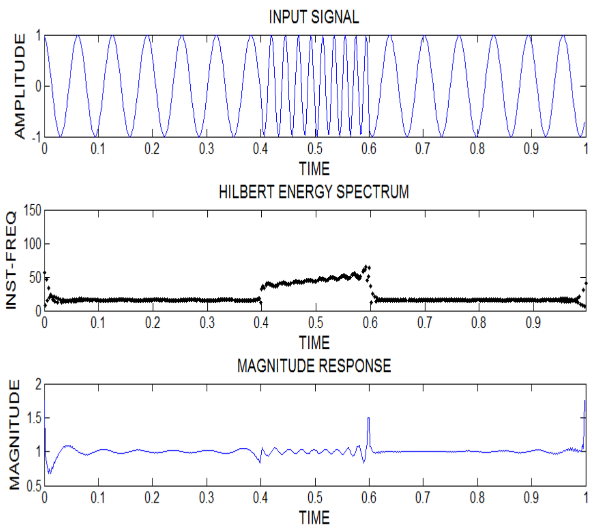

Fig. 4. Detection and visual localization of the Signal with Up Chirp

In the classification phase [12], the unknown patterns are presented to the root node. The class is obtained by moving down the tree. Starting from the root, the activation value of the current node provides the next node to be considered until reaching a leaf node that assigns the class of the input pattern. Each node applies the "winner-takes-all" rule.

Simulation Results. Here the test is characterized by a training set (TS) consisting of 900 patterns of each disturbance, distributed on a 2-D feature space with the features: Entropy Vs Standard Deviation that are extracted from the Hilbert Transformed Signal. The BNT that has been constructed constitutes of a root node, six internal nodes and eight leaf nodes shown in fig-5.

6 Conclusion

EMD is a promising method for non-stationary signal processing. It is used as a tool to extract IF information of each mode, thereby making it an important tool in the assessment of PQ events. The results reported here are believed to provide with new insights on EMD and its use. Apart from assessment, detection capability validates the potential of the algorithm. Finally, the Hilbert Energy Spectrum makes use of the Hilbert Transform which is an essential tool for conversion of signals into analyzable forms and to provide a useful, visual, qualitative understanding of a signal i.e. decomposed by EMD. The features that are extracted are applied to a Balanced Neural Tree for non-stationary power signal disturbance classification.

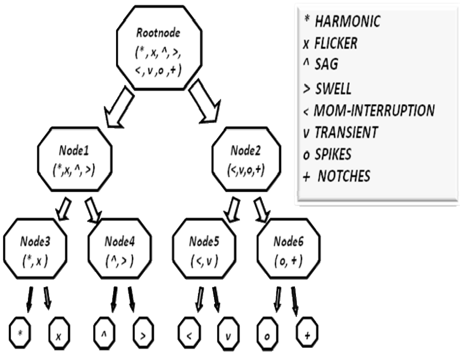

Fig. 5. Balanced Neural Tree.

Table 1. Classification Accuracy Table.

Disturbances	Classification Accuracy
Harmonic	95.75
Flicker	98
Sag	98
Swell	91.45
Momentary Interruption	100
Transient	100
Spikes	100
Notches	100
Overall Accuracy	97.9

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